The Meerkat Effect:

Personality and Market Returns Affect Investors' Portfolio Monitoring Behavior

Svetlana Gherzi[a]*, Daniel Egan[b], Neil Stewart[a], Emily Haisley[c], Peter Ayton[d],

[a]University of Warwick, Department of Psychology, Coventry CV4 7AL, UK
[b]Betterment, Betterment, LLC 247 Centre St., New York, NY 10013, US
[c]Barclays Wealth Management, London 1 Churchill Place, Canary Wharf, London E14 5HP, UK
[d]City University London, Department of Psychology, Northampton Square, London EC1V 0HB, UK

*Corresponding author: Svetlana Gherzi
Tel.:+44(0)779 618 5347; +44(0)247 657 3127
Email addresses: s.gherzi@warwick.ac.uk; neil.stewart@warwick.ac.uk

Abstract

Karlsson, Loewenstein and Seppi (2009) found that, following market downswings, investors are less likely to login to monitor their retirement portfolios. They concluded that, rather like (apocryphal) ostriches sticking their heads in the sand, investors avoid unpleasant information by reducing portfolio monitoring in response to news of negative market movement. We apply generalized non-linear mixed effects models to test for this selective information monitoring at an individual level in a new sample of active online investors. We see different behavior in this new sample. We find that investors *increase* their portfolio monitoring following both positive *and* daily negative market returns, behaving more like hyper-vigilant meerkats than head-in-the-sand ostriches. This pattern persists for logins not resulting in trades and weekend logins when markets are closed. Moreover, an investor personality trait – neuroticism - attenuates the pattern of portfolio monitoring suggesting that market–driven variation in portfolio monitoring is attributable to psychological factors.

Keywords:

Behavioral finance, individual investors, selective attention, personality, investment decisions, ostrich effect

JEL Classification
D81, D82, G02, G14

1. Introduction

A standard assumption of the economics of information is that we should place value on information to the extent that it serves as input to decisions that enable us to obtain desired outcomes. However, recent studies have suggested that we can also value information for its own sake, and derive positive and negative utility directly from information. Loewenstein (2006) discusses cases where individuals seek out or avoid additional information conditional on their expectations of how such information will make them feel, independent of its informational value. For example, in the medical domain Loewenstein, Read and Baumeister (2003) describe how people choose not to book an appointment to see a doctor in order to avoid receiving potentially threatening information about their medical condition even if such information could potentially provide information that would improve the quality of their health and wellbeing. Recent studies in neuroscience (Berns et al. 2006) show that regions of the brain that are activated during the experience of a painful electric shock are also activated in individuals anticipating the impending painful experience. The brain activation increases as the time of the shock approaches - behavior consistent with the notion that the information that one is going to receive an electric shock is, like the shock itself, a source of misery. Indeed, thinking about the shock was so unpleasant that subjects in this study preferred more pain - a higher voltage shock - in order to reduce the time they spent dreading the impending shock.

As well as avoiding negative information people may seek out and relish positive information. Ehrilch et al. (1957) found that owners who recently purchased cars were more attentive to advertisements for the model which they bought compared to the other models they had considered buying. Similarly, Brock and Balloun (1967) found that smokers made more effort to listen to pro-smoking messages than non-smokers, and non-smokers made more effort to listen to a message affirming the link between smoking and lung cancer than smokers. The evidence indicates that, for both positive and negative information, people seek out or avoid information contingent on their expectation of its hedonic impact.

A recent study by Karlsson, Loewenstein and Seppi (2009) has found evidence that people selectively seek out and avoid information in a behavioral finance context. Given that the hedonic disutility of attending to bad news may outweigh its informational benefits, Karlsson et al. (2009) built a model that brings together information acquisition and hedonic utility of information. The model predicts that individuals rapidly seek out definitive information given positive news and avoid information in the face of adverse news or in other words, that they will have asymmetric preferences for the timing and resolution of uncertainty.

In their study Karlsson et al. (2009) explored two datasets. The first dataset from the Swedish Premium Pension Authority represented Swedish citizens' investments in equity and interest-bearing funds for their pensions aggregated across all clients. The second dataset, provided by Vanguard Group, one of the largest investment management companies, aggregated American investors who primarily had personal 401(k) plans - retirement savings plans that can be invested into various funds. In both datasets the authors found that investors selectively attended to information, as shown by portfolio monitoring increasing with rising markets. Karlsson et al. (2009) reported evidence that investors check the value of their portfolios more frequently following positive market movements. In the US dataset prior averaged market return[1] of 1% increased the daily mean number of logins by 5-6% and in the Swedish dataset by 1%.

Borrowing from an earlier study by Galai and Sade (2006), Karlsson et al. (2009) termed this pattern of information monitoring the *ostrich effect*. Galai and Sade's (2006) identification of the ostrich effect stems from their finding that the return on liquid assets was greater than that on equally risky illiquid assets and that this difference in returns was higher in periods of greater uncertainty. Galai and Sade (2006) attributed this observation to investors' willingness to pay a premium for the "bliss of ignorance" (p. 2758). Under a standard economic account people should demand a higher return for the illiquid assets, all other things being equal. The finding of the opposite pattern suggests that both because information about losses is particularly painful, and because information about the performance of illiquid assets is less accessible, investors are more willing to hold illiquid assets. Accordingly, Galai and Sade (2006) attributed investors' preference for illiquid assets over equally risky liquid assets to the avoidance of potentially negative or uncertain information.

More recently, using the same dataset as Karlsson et al. (2009), Sicherman, Loewenstein, Seppi and Utkus (2013) have extended the analysis of Vanguard clients' (mostly 401k) accounts over the 2007-2008 period to an individual account-level introducing a non-linear function (cf. Karlsson et al. 2009, who used a linear function) to relate market returns to logins to examine possible differences between the effect of positive

[1] Karlsson et al. (2009) define prior averaged market returns as the log change in the index relative to the average index level over the previous 4 days.

and negative returns. Sicherman et al. (2013) confirmed the ostrich effect reporting a significant negative coefficient on a “down Dow” dummy variable which indicated whether the Dow index went down on the previous day. However, they found no corresponding increase in monitoring when the Dow increased; in fact monitoring slightly decreased across the range of positive returns. They confirmed the ostrich effect for negative market returns at both an aggregate and individual level; although many individual accounts had too few logins to enable detection of any effect, about 14% of their sample showed a significant return / login relation and, of these, 79% of investors showed the ostrich effect, while 21% were “anti” ostriches as they had the opposite response to the market returns (increasing logins given negative market returns). Moreover, consistent with the view that the ostrich effect has a psychological basis, Sicherman et al. (2013) find that ostrich behavior is a relatively stable personal characteristic over time; individuals who displayed ostrich behavior in 2007 were more likely to display ostrich behavior in 2008.

In this study we test the effects of market returns on individual investors’ portfolio monitoring decisions in a new data set. Our data set is from 617 UK private individuals investing in equities from 2004-2009, and contrasts with the Vanguard and Swedish Premium Pension Authority investors allocating into pension funds in 2007-2008. We consider the effects of positive and negative daily market returns separately over a 6 year time period. To preview our results, like Karlsson et al. (2009) and Sicherman et al. (2013), we find that login behavior depends on market returns, but in our data the dependency is quite different. Rather than the ostrich effect pattern, where people login less after recent negative market returns, we find what we term a *meerkat effect* in which people login *more*, not less, in response to recent negative returns - *as well as* to positive returns.

In attempting to understand why login behavior should vary as a function of market returns we assume that investor logins may be motivated by different intentions. They may login to trade or merely for portfolio information. Regardless of a trader’s intentions both of these kinds of login could result in a trade - or not. In our modelling as well as considering all logins, we also consider just the subset of logins that did not result in a trade. This is because although logins that did not result in a trade do not necessarily reflect hedonic monitoring, these transaction-free logins can be considered more likely to reflect informational portfolio monitoring. We find that, for such non-trade logins investors increase their portfolio monitoring given both positive *and* negative daily market returns. To test this idea further we analyse weekend logins, days when investors cannot transact. We again find investors increase their portfolio monitoring for both positive *and* negative daily market returns - *a meerkat effect.* The fact that non-trade logins increase with positive daily market returns is consistent with the idea that investors seek - and gain - hedonic utility directly from positive information. However our findings of increased logins with negative market returns for daily non-trade logins and weekend logins are again the opposite of the ostrich effect for negative market returns found by Sicherman et al. (2013).

Karlsson et al. (2009) and Sicherman et al. (2013) propose that the ostrich effect is attributable to psychological factors, and our study was originally planned to seek corroborative evidence for this notion by exploring the possibility of a link between the psychological trait of neuroticism and individual differences in login behavior. The personality trait of neuroticism is associated with high levels of anxiety. While anxiety can be a mood or an emotion, *trait* neuroticism describes individual differences in base-line levels of anxiety; indeed some authors refer to anxiety as a personality trait (Wilt, Oehlberg & Revelle 2011). Neuroticism is one of the major human personality traits identified in the five factor model of personality (Costa & McRae 1992) and as more neurotic individuals experience greater anxiety and worry (Mathews, Deary & Whiteman 2003), we envisaged that this would be reflected in their reactions to negative market returns. In order to investigate the psychological basis of the ostrich effect, we construct a measure of the neuroticism personality trait for each investor and test whether investors' level of neuroticism interacts with the effect of daily market returns on logins. We hypothesise that there will be individual differences in logins conditional on the daily market returns. The next section introduces our dataset, definitions of variables, descriptive statistics and the generalized mixed effects model. Section 3 presents the results. In Section 4 we introduce the trait of neuroticism and its interaction with the meerkat effect. Discussion is presented in Section 5.

2. Dataset and Methodology

2.1 Data and sample characteristics

We study 617 clients from Barclays Wealth Management. For each client we have their logins and trading records over a 6 year period (2004-2009) and their self-reported demographics derived from a survey of the same 617 investors. The survey was conducted in a series of waves from September 2008 to December 2009 in order to explore investors' attitudes and disposition in relation to financial markets that were of interest to Barclays Wealth Management research objectives. As an incentive to participate in the survey respondents were promised a summary of the research findings. Overall, such survey methodology has become an important addition to finance (Graham & Harvey 2001, Lins, Servaes & Tufano 2010).

In this study our sample of investors was selected based on the activity and wealth of individual investors. Those with more than 1 trade per year and those with portfolio value of more than £1000 were invited to participate in the survey with a total of 19,251 of their clients invited to take part in an online survey via email. 4,520 clients opened the email and 849 proceeded to the on-line questionnaire survey. 617 clients completed the survey, which is in the same range of response rate as in similar studies by Dorn and Huberman (2005) and Glaser and Weber (2007).

Figure 1 provides demographic distributions of the panel sample of our 617 investors who took part in the survey and includes investors' age, number of dependents, investable wealth, income and marital status and the demographic survey questions. To identify potential selection biases, we compared survey participants to an adult British population based on the data reported by the Office for National Statistics. Overall our 617 investors have above average incomes compared to the British population; while the mean British income is around £30,000 our sample has a mean of £76,616 and a median of £60,000. 84% of the sample are the prime financial (investment and savings) decision makers of the household. The average age of survey participants is 51 years, four years older than the average British adult. Survey participants are also more likely to be married (0.74 vs. 0.52) or male (0.93 vs. 0.49) compared to the British average. Although our respondents are not representative of the typical British adult, their demographics are in-line with private investor populations analysed in other studies (Dorn & Huberman 2005).

Figure 2 plots the distributions of the daily market returns as measured by FTSE100 Index, the average daily number of logins per investor and the daily average number of logins per investor excluding those logins that resulted in a trade, or as we refer to, informational / hedonic logins. Investors in the sample login on 37% of the trading days. Figure 3 is a raw scatter plot of aggregate number of daily logins and daily market returns; the locally weighted scatterplot smoothing line clearly indicates non-linearity in the data showing increased logins responses to both market gains and losses.

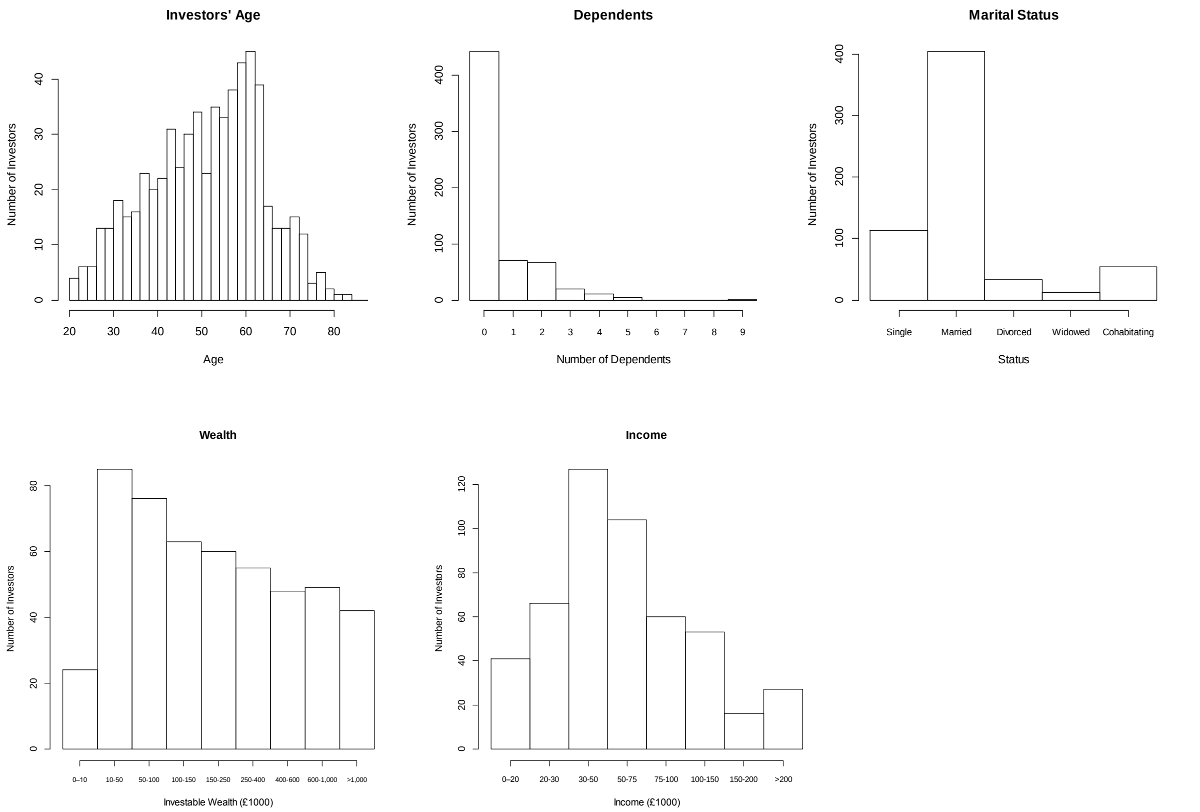

Figure 1. Demographics distributions: investors' age, number of dependents investors have, marital status, investable wealth and income. The survey questions were phrased as follows: How old are you? How many dependents do you have? What is your marital status? (Single; Married; Divorced; Widowed; Cohabitating). What is the approximate total value of all of your investable wealth - your stocks, bonds, investment funds, derivatives and cash holdings? What is your expected gross annual income for this year?

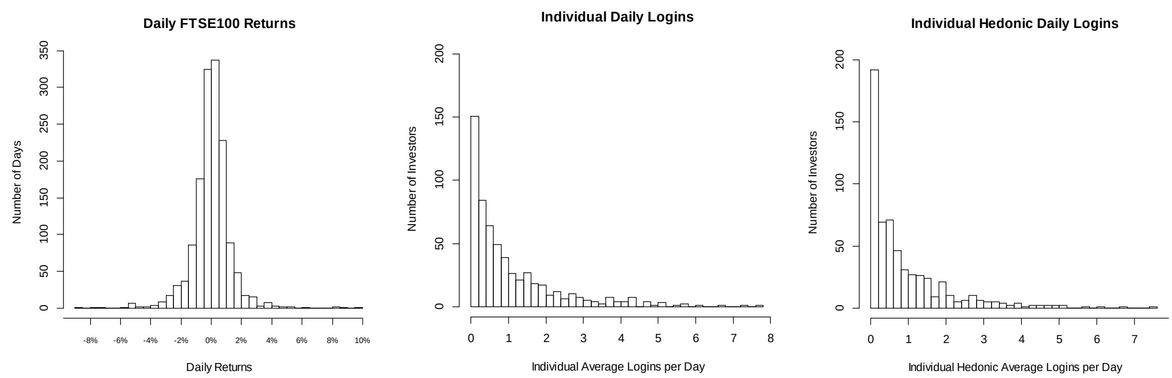

Figure 2. FTSE100 Index and logins distributions (trading days): FTSE100 Index ranging from January 2004 to December 2009 to match the transactions data, average daily logins per investor, average daily logins per investor excluding logins that resulted in a trade. Daily Market Returns = (FTSE100 Price $_{(t)}$ - FTSE100 Price $_{(t-1)}$) / FTSE100 Price $_{(t-1)}$. Closing prices are applied.

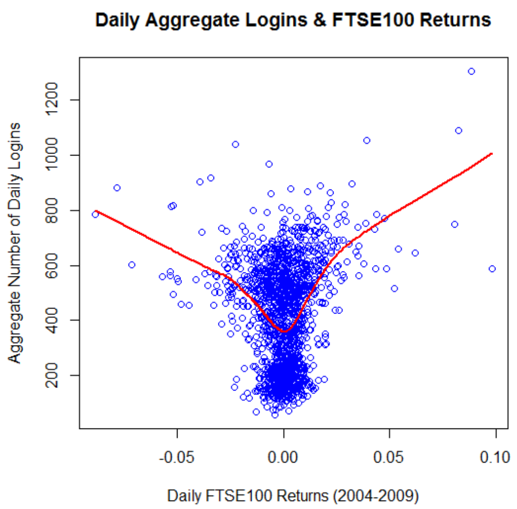

Figure 3. Aggregate logins and daily returns: The scatter plot shows the aggregate number of daily logins of our sample of investors and the daily FTSE100 returns with locally weighted scatterplot smoothing line.

2.2 Models:

Our data allows us to measure investors' portfolio monitoring behavior at an individual rather than the aggregate level. While we later describe analyses of logins that did not result in trades our first analysis includes all trading day logins. All models in this study include the full sample of 617 investors. Given that we have count data (the number of logins) we use a Poisson model and because we have repeated measures for each client we use a mixed effects model. This Poisson mixed effects model has random intercepts to account for each investor's propensity to login to their portfolio and random slopes to account for individuals' sensitivity to daily market returns. To directly test the sensitivity of investors' login behavior to changes in daily market returns separately for positive and negative domains, we use two dummy variables to indicate the sign of daily market returns, one to indicate a positive return (Up-Dummy) and one to indicate a negative return (Down-Dummy). We control for days of the week, age, gender, income, marital status and whether the individual is the prime financial decision maker in the household. We exclude weekends and holidays from the first part of the analysis as the stock market is closed therefore allowing us to focus on trading days; we consider weekend monitoring behavior in a later section 3.5. We fit four models. The first model uses daily market returns - returns between yesterday's and today's closing price - as the independent variable. The second model uses a 5-day moving average of daily market returns and the third model uses a 20-day moving average. The 5-day market return is the average of daily market returns for the week. For example if today is a Wednesday, the 5-day returns calculation would include daily market returns on the last Thursday though today. A similar method is used for the 20-day market returns calculation. It makes sense to look at market returns over several time periods: a recent daily return, a week's average return and a month's average return could cause varied portfolio monitoring behavior. The fourth model includes previous day's logins since a login on Tuesday might not be independent from a login on Monday. All four models gave very similar results.

3. Results

3.1 Daily Market Returns

The results in Table 1 show coefficients from our four Poisson mixed effects models. Across all models there are more logins on Mondays and Tuesdays compared to the rest of the trading days (Friday was the baseline in our regressions). There is also a significant gender effect in all models with males logging in more frequently, which is consistent with Sicherman et al.'s (2013) results. In Model 1, the significant positive coefficient for the interaction between daily market returns and the dummy for positive returns (Returns×Up-Dummy) indicates that given an increase in daily market returns investors monitor their portfolios more. The significant negative coefficient for the interaction between daily market returns and the dummy for negative daily market returns (Returns×Down-Dummy) indicates that the pattern is significantly different in the loss domain. Investors login more often with increasingly positive daily market returns and more, *not less*, after increasingly negative daily market returns. We call the increased monitoring as a function of increasing absolute daily market returns the *meerkat effect*[2] because investors increase their monitoring given changes. A t-test confirms that the absolute steepness of the slopes is significantly different ($p<.001$) in positive and negative domains. In summary, investors increase portfolio monitoring given both positive *and* negative daily market returns. The observed increase in portfolio monitoring given positive daily market returns is consistent with the ostrich effect; however, the increase in logins for negative daily market returns (relative to zero returns) is not consistent with what would be expected from an aversion to negative information.

[2] Typically one meerkat is on guard duty. Once faced with danger all meerkats come up and immediately begin jumping and growling.

3.2 Past Daily Market Returns

Model 2 replicates the analysis of Model 1, but replaces the daily market returns with the 5-day moving average, and we find the same significant meerkat effect – that is increased portfolio monitoring for both positive and negative market returns. Model 3 uses a 20-day moving average instead of the 5-day moving average and again we find the same significant pattern. Model 4 extends Model 1 by including a lagged login and it is consistent with the previous three models and shows that those investors who are more likely to login in the past are more likely to login today.

Table 1

Poisson Models of All Weekday Logins

	Model 1 Daily Ret	P Value	Model 2 5-day Ret	P Value	Model 3 20-day Ret	P Value	Model 4 Login lag	P Value
(Intercept)	-1.004	0.007	-0.959	0.011	-0.949	0.011	-1.153	0.001
Monday	0.047	0.000	0.056	0.000	0.056	0.000	0.039	0.000
Tuesday	0.011	0.008	0.015	0.000	0.011	0.007	0.018	0.000
Wednesday	-0.011	0.008	-0.009	0.023	-0.012	0.004	-0.012	0.004
Thursday	-0.002	0.692	-0.007	0.096	-0.007	0.067	-0.002	0.592
Age	-0.004	0.383	-0.004	0.365	-0.004	0.361	-0.004	0.327
Decision Maker	-0.011	0.899	-0.011	0.901	-0.011	0.901	-0.014	0.867
Gender (Male)	0.615	0.011	0.611	0.012	0.611	0.012	0.563	0.011
Income	0.000	0.030	0.000	0.029	0.000	0.029	0.000	0.027
Married	-0.009	0.957	-0.007	0.965	-0.007	0.967	0.008	0.959
Divorced	-0.149	0.596	-0.147	0.602	-0.146	0.603	-0.126	0.622
Widowed	0.109	0.803	0.114	0.794	0.115	0.794	0.181	0.651
Cohabitating	0.373	0.118	0.374	0.117	0.374	0.117	0.337	0.121
Returns×Up Dummy	5.758	0.000					5.504	0.000
Returns×Down Dummy	-2.207	0.000					-1.567	0.000
Return 5-days×Up Dummy			4.997	0.000				
Return 5-days×Down Dummy			-1.669	0.000				
Return 20-days×Up Dummy					2.088	0.003		
Return 20-days×Down Dummy					-4.620	0.000		
Login 1 day lag							0.142	0.000
Marginal R^2	1.2%		1.2%		1.2%		3.0%	
Conditional R^2	48%		48%		48%		45%	

Note: The marginal R^2 describes the proportion of variance explained by the fixed factor(s) alone. The conditional R^2 describes the proportion of variance explained by both the fixed and random factors.

3.3 Hedonic monitoring

When people login they may do so with the intention of monitoring only or the intention of trading, and then once logged in, then can trade or not. Thus we have a 2x2 table of scenarios: (i) intending to trade and then trading, (ii) intending to trade but not trading, (iii) intending to monitor but then trading, and (iv) intending to monitor and then not trading. Of course, unfortunately, we do not know the intention at login, only the result - either a trade or not. We differentiate between portfolio logins for trading purposes versus pure informational purposes to explore the psychological effects of information. As non-trade logins can be considered more likely to reflect informational portfolio monitoring we subtract days with logins that resulted in a trade (trading days) from the dataset for each investor and conduct similar analyses as above to test the relationship between login days not involving transactions and daily market returns. Karlsson et al. (2009) addressed this issue by using the number of account logins less the number of portfolio reallocations in the Swedish dataset and aggregate S&P 500 trading volume as a proxy to control for transactional logins in the Vanguard dataset. Sicherman et al. (2013) also controlled for how much investors trade and performed analyses of weekend logins, which we consider in a later section.

Table 2 reports results from our four non-trade logins Poisson models. The Returns×Up-Dummy coefficients are, as before, significantly positive across all four model specifications suggesting investors' increased demand for positive information given rising markets. The fact that there are logins that do not result in trades is not, by itself, necessarily indicative of hedonic monitoring. However the observed *increase* in non-trade logins as a function of rising markets does support the notion that investors seek and obtain positive utility directly from information. Investors are more likely to monitor their portfolio given rising markets.

Given falling markets, the significant Returns×Down-Dummy coefficient in Model 1 implies that in response to daily market decreases, investors increasingly seek-out information; this is counter to the ostrich effect supporting our coining of the term meerkat effect. Model 4, which is similar to Model 1, but includes a term to control for the influence of logins on the previous day, also shows a meerkat effect. This model also shows that investors' login decisions are not independent of their logins the day before. However, Model 2 (the 5-day average return specification) shows the opposite pattern for these non-trade logins to that observed when logins involving trades were included. Instead of the meerkat effect there is a mild ostrich effect, such that with increasingly negative returns fewer non-trade logins are made. This possibly reflects the fact that because there is a larger proportion of logins that result in a trade when market declines (cf. Figure 4) there would be fewer opportunities for investors to record login days without trading over the 5-day period. Figure 4 shows a plot of the proportion of trades given a login across daily market returns and confirms that in falling markets investors' logins are increasingly likely to result in transactions; for rising markets the increase in transactions per login is not so steep. Model 3 (the 20-day return specification) shows that when the market declined over the previous month, investor logins without trades do not vary from their baseline level.

Table 2

Poisson Models of Non-Trades Weekday Logins

	Model 1 Daily Ret	P Value	Model 2 5-day Ret	P Value	Model 3 20-day Ret	P Value	Model 4 Login lag	P Value
(Intercept)	-1.297	0.001	-1.260	0.001	-1.253	0.002	-1.712	0.000
Monday	0.047	0.000	0.054	0.000	0.055	0.000	0.075	0.000
Tuesday	0.018	0.000	0.022	0.000	0.019	0.000	0.020	0.067
Wednesday	-0.002	0.678	-0.002	0.724	-0.003	0.493	-0.015	0.166
Thursday	0.007	0.145	0.002	0.586	0.002	0.677	0.003	0.803
Age	-0.003	0.570	-0.003	0.549	-0.003	0.544	-0.002	0.753
Decision Maker	0.005	0.957	0.005	0.954	0.005	0.954	-0.015	0.868
Gender (Male)	0.604	0.018	0.600	0.019	0.600	0.019	0.566	0.022
Income	0.000	0.021	0.000	0.021	0.000	0.021	0.000	0.015
Married	-0.002	0.989	-0.002	0.993	-0.001	0.994	-0.108	0.520
Divorced	-0.111	0.708	-0.109	0.714	-0.109	0.714	-0.207	0.469
Widowed	-0.055	0.905	-0.049	0.916	-0.049	0.916	-0.100	0.823
Cohabitating	0.409	0.103	0.409	0.103	0.409	0.103	0.195	0.421
Returns× Up Dummy	5.399	0.000					9.685	0.000
Returns× Down Dummy	-0.447	0.007					-2.104	0.000
Return 5-days×Up Dummy			5.431	0.000				
Return 5-days×Down Dummy			1.828	0.000				
Return 20-days×Up Dummy					4.887	0.000		
Return 20-days×Down Dummy					0.376	0.638		
Login 1 day lag							1.712	0.000
Marginal R^2	1.2%		1.2%		1.2%		16%	
Conditional R^2	51%		51%		51%		57%	

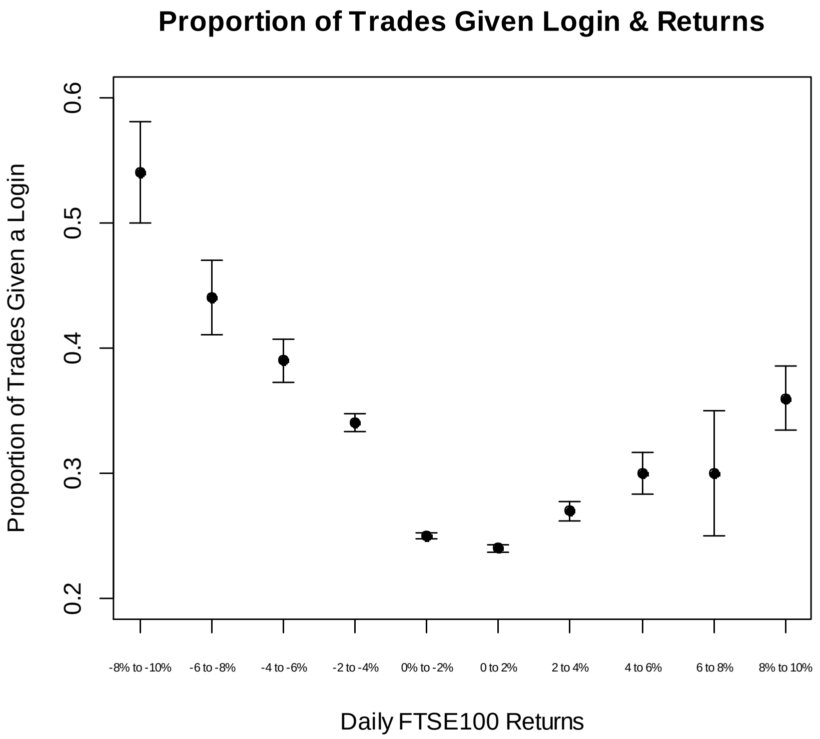

Figure 4. The plot shows proportion of daily trades given a login for daily market returns with bars showing the 95% confidence intervals.

3.4 Robustness tests

Because the system automatically logs-off inactive investors, multiple logins per day do not necessarily indicate a greater interest in portfolio monitoring; the most active investors could login just once and remain logged in - and monitoring - all day, while investors with a higher number of logins might be monitoring less and so being repeatedly logged out. For these reasons we tested a logit mixed effects model with a binary dependant variable for daily portfolio monitoring – measuring a login if an investor logged into his account any number of times on that day or no-login if an investor did not login on that day. As previously, we fitted four models for all logins (Table 3) and for non-trade logins (Table 4). Table 3 reports similar results to the Poisson models reported in Table 1 except that the returns and Down-Dummy interaction coefficients for Model 3 and Model 4 are non-significant. Results of the non-trade logins logit regressions in Table 4 are similar to the corresponding Poisson model specifications in Table 2 – except the returns and Down-Dummy interaction variable for Model 4 is non-significant. Though some effects are not significant over longer averaged returns the different criterion for logins tested with the logit models does not change the overall pattern of effects we observe.

Table 3

Logit Models of All Weekday Logins

	Model 1 Daily Ret	P Value	Model 2 5-day Ret	P Value	Model 3 20-day Ret	P Value	Model 4 Login lag	P Value
(Intercept)	-1.061	0.029	-0.991	0.041	-0.973	0.045	-1.430	0.000
Monday	0.063	0.000	0.074	0.000	0.076	0.000	0.039	0.000
Tuesday	0.040	0.000	0.049	0.000	-0.003	0.771	-0.012	0.010
Wednesday	-0.001	0.885	0.002	0.843	0.041	0.000	-0.006	0.186
Thursday	0.004	0.689	-0.002	0.816	-0.002	0.862	0.003	0.477
Age	-0.002	0.774	-0.002	0.742	-0.002	0.733	-0.003	0.487
Decision Maker	-0.022	0.847	-0.022	0.851	-0.022	0.850	0.000	0.999
Gender (Male)	0.687	0.029	0.683	0.030	0.681	0.030	0.552	0.018
Income	0.000	0.016	0.000	0.015	0.000	0.015	0.000	0.028
Married	-0.134	0.533	-0.133	0.536	-0.132	0.537	0.010	0.949
Divorced	-0.276	0.450	-0.272	0.457	-0.271	0.458	-0.097	0.720
Widowed	-0.149	0.794	-0.140	0.806	-0.138	0.808	0.010	0.982
Cohabitating	0.253	0.413	0.252	0.415	0.252	0.415	0.365	0.112
Returns×Up Dummy	9.221	0.000					5.293	0.000
Returns×Down Dummy	-3.954	0.000					-0.050	0.768
Return 5-days×Up Dummy			10.380	0.000				
Return 5-days×Down Dummy			-1.839	0.019				
Return 20-days×Up Dummy					9.784	0.000		
Return 20-days×Down Dummy					-2.805	0.111		
Login 1 day lag							0.150	0.000
Marginal R^2	1.3%		1.2%		1.2%		3.0%	
Conditional R^2	62%		61%		61%		48%	

Table 4

Logit Models of Non-Trades Weekday Logins

	Model 1 Daily Ret	P Value	Model 2 5-day Ret	P Value	Model 3 20-day Ret	P Value	Model 4 Login lag	P Value
(Intercept)	-1.295	0.009	-1.231	0.013	-1.221	0.014	-1.902	0.000
Monday	0.059	0.000	0.069	0.000	0.071	0.000	0.063	0.000
Tuesday	0.048	0.000	0.056	0.000	0.007	0.514	0.029	0.012
Wednesday	0.011	0.295	0.014	0.202	0.050	0.000	-0.003	0.792
Thursday	0.013	0.222	0.008	0.474	0.011	0.318	0.012	0.299
Age	-0.001	0.868	-0.001	0.836	-0.001	0.834	-0.001	0.834
Decision Maker	-0.008	0.949	-0.007	0.952	-0.007	0.953	-0.003	0.977
Gender (Male)	0.662	0.039	0.654	0.041	0.653	0.042	0.539	0.035
Income	0.000	0.013	0.000	0.013	0.000	0.013	0.000	0.014
Married	-0.132	0.547	-0.131	0.550	-0.131	0.551	-0.107	0.541
Divorced	-0.246	0.510	-0.243	0.515	-0.242	0.516	-0.181	0.542
Widowed	-0.260	0.655	-0.255	0.662	-0.253	0.664	-0.221	0.633
Cohabitating	0.279	0.378	0.278	0.380	0.278	0.379	0.225	0.371
Returns×Up Dummy	8.683	0.000					9.311	0.000
Returns×Down Dummy	-2.105	0.000					-0.413	0.326
Return 5-days×Up Dummy			11.080	0.000				
Return 5-days×Down Dummy			2.265	0.007				
Return 20-days×Up Dummy					12.500	0.000		
Return 20-days×Down Dummy					2.431	0.199		
Login 1 day lag							1.675	0.000
Marginal R^2	1.3%		1.2%		1.2%		15%	
Conditional R^2	62%		62%		62%		57%	

3.5 Weekend Monitoring

Our second strategy for examining psychological effects of information is to use weekend logins. As the market is closed at weekends we assume weekend logins will not be motivated by any intent to trade; with the exception of placing limit orders and market orders for immediate execution once the market opens, investors will be restricted to monitoring. Accordingly we investigated weekend logins using similar models as reported in previous sections. Treating the weekend as one period Table 5 reports results for weekend logins regressed on the previous Friday's returns using both Poisson and logit models (Model 1a and Model 1b). For the logit model we measured a login if an investor logged into his account any number of times on that weekend (Saturday or Sunday) or no-login if an investor did not login on that weekend.

Across both models we find support for the meerkat effect as investors significantly increase monitoring given both positive and negative market returns. We also used a similar strategy to test the effect of the previous week's returns on weekend monitoring behavior in Model 2a (Poisson) and 2b (logit). The only significant coefficient for these two models is a negative significant coefficient for the 5-day Return×Up-Dummy in Model 2a indicating that when the week is looking good investors chose not to monitor at the weekend – counter to both the meerkat and ostrich effects. This finding is difficult to interpret and different to what we have observed for the 5-day return on trading days – with or without excluding non-trade logins.

Table 5

Weekend Logins

	Model 1a		Model 1b		Model 2a		Model 2b	
	Poisson	P Value	Logit	P value	Poisson	P Value	Logit	P value
(Intercept)	-2.212	0.000	-2.607	0.000	-2.172	0.000	-2.545	0.000
Age	0.008	0.088	0.011	0.036	0.008	0.093	0.011	0.040
Decision Maker	-0.003	0.967	0.011	0.908	-0.002	0.984	0.012	0.901
Gender (Male)	0.342	0.137	0.479	0.066	0.339	0.140	0.476	0.068
Income	0.000	0.003	0.000	0.011	0.000	0.003	0.000	0.011
Married	-0.197	0.204	-0.180	0.304	-0.195	0.208	-0.179	0.306
Divorced	-0.679	0.011	-0.668	0.026	-0.668	0.012	-0.665	0.027
Widowed	-0.231	0.576	-0.279	0.550	-0.223	0.589	-0.272	0.560
Cohabitating	0.271	0.224	0.317	0.209	0.267	0.231	0.316	0.210
Returns×Up Dummy	1.928	0.011	4.279	0.000				
Returns×Down Dummy	-3.013	0.000	-4.835	0.000				
Returns 5-days×Up Dummy					-5.481	0.002	-3.019	0.273
Returns 5-days× Down Dummy					-0.150	0.915	-0.058	0.979
Marginal R^2	1.7%		1.8%		1.7%		1.8%	
Conditional R^2	45%		51%		45%		51%	

3.6 Double Weekend Logins

If investors login and check their accounts on Saturday and then login again on Sunday, Sicherman et al. (2013) hypothesize they are doing this more for psychological reasons rather than purely to get additional portfolio information since prices have not changed. Accordingly, like Sicherman et al. (2013), we investigated double weekend logins by fitting a logit model with 1= login happened consecutively on a Saturday and a Sunday and 0 otherwise. Results are reported in Table 6. A model regressed on the previous Friday's returns (Model A) shows a meerkat effect – double weekend logins increased for both increasing and decreasing Friday returns. No significant effects on double weekend logins were measurable based on the average market returns over the prior 5-day period (Model B).

Table 6

Double Logins

	Model A Friday Returns	P value	Model B Week Returns	P value
(Intercept)	-4.859	0.000	-4.826	0.000
Age	-0.004	0.661	-0.004	0.607
Decision Maker	0.001	0.995	0.003	0.988
Gender (Male)	0.699	0.163	0.716	0.156
Income	0.000	0.016	0.000	0.014
Married	-0.537	0.066	-0.485	0.100
Divorced	-0.907	0.068	-0.826	0.098
Widowed	-0.503	0.533	-0.403	0.619
Cohabitating	0.054	0.891	0.118	0.765
Returns×Up Dummy	5.549	0.081		
Returns×Down Dummy	-6.438	0.007		
Returns 5-days×Up Dummy			-8.024	0.285
Returns 5-days×Down Dummy			-5.916	0.304
Marginal R^2	2.7%		3.6%	
Conditional R^2	65%		65%	

4. Psychology of selective attention

4.1 Neuroticism

The psychological evidence that motives and expectations impinge upon human perception to the extent that people's attention and information gathering are influenced by the emotional content of information has been accumulating since the 1940s. For example Postman, Bruner and McGinnis (1948) observed that individuals subconsciously raised the sensory thresholds for the conscious recognition of "unacceptable stimulus objects" terming the phenomenon perceptual defence. Exploring this phenomenon further McGinnis (1949) measured participants' psychophysiological indicators (galvanic skin response) to assess people's emotional reactions and found that there was a selective emotional response to threatening stimuli - but not neutral ones. McGinnis concluded that: "perceptual defence is designed to delay the greater anxiety that accompanies actual recognition of the stimulus" (p.250). Anxiety is directly associated with a trait of neuroticism (Mathews, Deary & Whiteman 2003). *Trait* neuroticism describes individual differences in base-line levels of anxiety; indeed some authors refer to anxiety as a personality trait (Wilt et al. 2011). As earlier research has found that more neurotic people tend to be more perceptually defensive (e.g. Watt & Morris 1995) we hypothesize that the trait of neuroticism plays a role in portfolio monitoring behavior. At the time of planning this study we envisaged we would replicate the ostrich effect and then be able to measure its association with neuroticism. Such a result would offer direct corroboration of Karlsson et al.'s (2009) suggestion, that variation in portfolio monitoring with market returns is attributable to psychological factors. Although we have not replicated the ostrich effect, the rationale for studying the relationship between personality and variation in portfolio monitoring with market returns applies equally well to the meerkat effect. Indeed, some authors have proposed that the attentional system of anxious individuals is abnormally sensitive to threat-related stimuli and that these individuals tend to direct their attention toward threatening information (Williams, Watt, MacLeod & Matthews 1988).

4.2 Survey

The single measure of neuroticism was reported by the 617 investors as part of the survey questions collected by Barclays Wealth Management. Although the survey was conducted during turbulent financial times, it is well evidenced that personality traits are stable in adulthood and are seen as important inputs into social and economic outcomes by both psychologists and economists (Cobb-Clark & Shrurer 2011; Heineck & Anger 2010; Mueller & Plug 2006; Nyhus & Pons 2005). In the survey, which is based on the five-factor model of personality inventory (Costa & McRae 1992), each investor responded on a 1-7 Likert scale (labelled 1 "strongly disagree" to 7 "strongly agree"; 4 was labelled "neither agree or disagree") to four personality statements. The resulting scores ranged from 4 to 28 points and then were scaled to have a mean of 0 and standard deviation of 1. Figure 5 reports the distribution of neuroticism and the survey statements used to construct the measure.

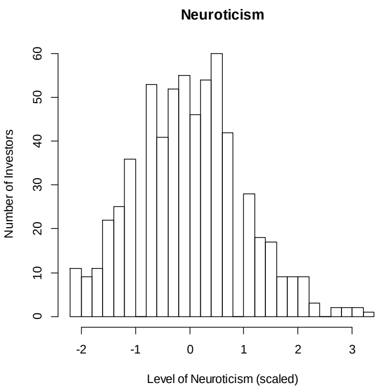

Figure 5. Distribution of trait neuroticism from least neurotic to most neurotic (scaled). Survey questions include the following: I am not easily bothered by things. I fear for the worst. I get stressed easily. Uncertainty makes me uneasy, anxious or stressed.

4.3 Personality Results

We apply similar analysis as in Section 3 using mixed effects with neuroticism added as a fixed effect variable into the model. As a robustness check we carried out both Poisson and logit regressions. As before, we also consider models with all logins and models with logins that did not result in a trade separately. Table 7 reports results for four models using the daily returns specification as in Model 1 in Section 3. The first and second columns report Poisson and logit models respectively with all logins. The third and fourth columns report Poisson and logit models with logins that did not result in a trade. The coefficient for Neurotic is negative but non-significant across all models, however of interest is the significant interaction between neuroticism and negative market returns (Returns×Neurotic×Down-Dummy) across all model specifications; the rate of increase in monitoring with negative market returns we characterise as the meerkat effect is more extreme for neurotic investors.

For positive market returns all logins and non-trade logins show that the rate of increase in logins is gentler for more neurotic investors. However this interaction is only significant for the Poisson model specifications (Models 1a and 1c). Figure 6 plots the fixed effects of returns, neuroticism, and their interactions from Model 1a.

Table 7

Poisson and Logit Models of Weekday Logins with Neuroticism

	Model 1a Poisson All logins	P Value	Model 1b logit All logins	P Value	Model 1c Poisson Non-Trade Logins	P Value	Model 1d logit Non-Trade Logins	P Value
(Intercept)	-1.005	0.007	-1.064	0.028	-1.298	0.001	-1.293	0.009
Monday	0.047	0.000	0.063	0.000	0.047	0.000	0.059	0.000
Tuesday	0.011	0.008	0.040	0.000	0.007	0.146	0.013	0.223
Wednesday	-0.011	0.008	-0.001	0.886	0.018	0.000	0.048	0.000
Thursday	-0.002	0.691	0.004	0.689	-0.002	0.673	0.011	0.295
Age	-0.004	0.416	-0.001	0.828	-0.003	0.596	-0.001	0.905
Decision Maker	-0.013	0.888	-0.025	0.832	0.004	0.964	-0.010	0.936
Gender (Male)	0.602	0.013	0.669	0.033	0.595	0.020	0.645	0.045
Income	0.000	0.027	0.000	0.014	0.000	0.020	0.000	0.012
Married	-0.005	0.977	-0.128	0.550	-0.001	0.997	-0.127	0.561
Divorced	-0.145	0.605	-0.269	0.461	-0.109	0.713	-0.241	0.518
Widowed	0.094	0.831	-0.172	0.763	-0.066	0.887	-0.279	0.632
Cohabitating	0.379	0.112	0.261	0.399	0.412	0.101	0.285	0.367
Neurotic	-0.053	0.361	-0.091	0.224	-0.038	0.537	-0.075	0.326
Returns×Up Dummy	5.727	0.000	9.235	0.000	5.380	0.000	8.696	0.000
Returns×Down Dummy	-2.219	0.000	-3.922	0.000	-0.456	0.006	-2.051	0.000
Returns×Neurotic×Up Dummy	-0.504	0.000	-0.516	0.161	-0.486	0.001	-0.431	0.272
Returns×Neurotic×Down Dummy	-0.364	0.008	-1.130	0.002	-0.781	0.000	-1.440	0.000
Marginal R^2	1.2%		1.5%		1.2%		1.4%	
Conditional R^2	48%		61%		51%		61%	

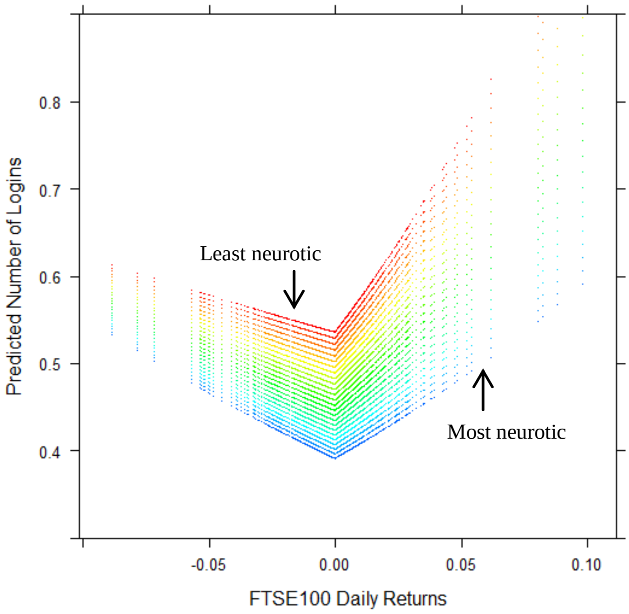

Figure 6. Number of logins and daily market returns: The plot illustrates predicted number of logins as a function of daily market returns and highlights effects of neuroticism, daily market returns and their significant interaction. The upper line represents those who scored the lowest on neuroticism and the lower line represents those who scored the highest on neuroticism.

4.4 Weekend monitoring and neuroticism

Conducting similar analysis as in the weekend monitoring section we find that neurotic investors login significantly less on the weekends across all model specification, however there are no interactions of neuroticism with market returns (see Table 8). We also find no interaction of neuroticism with market returns for double weekend logins. Given that neuroticism interacts with daily returns on weekdays, future research should explore the relationship between trading and the trait of neuroticism.

Table 8

Weekend Logins with Neuroticism

	Model 1a Poisson	P Value	Model 1b Logit	P value	Model 2a Poisson	P Value	Model 2b logit	P value
(Intercept)	-2.287	0.000	-2.696	0.000	-2.248	0.000	-2.640	0.000
Age	0.008	0.067	0.011	0.026	0.008	0.072	0.011	0.028
Decision Maker	-0.006	0.942	0.008	0.933	-0.005	0.955	0.009	0.926
Gender (Male)	0.314	0.170	0.443	0.088	0.312	0.174	0.441	0.090
Income	0.000	0.002	0.000	0.008	0.000	0.002	0.000	0.008
Married	-0.186	0.227	-0.166	0.342	-0.187	0.226	-0.168	0.335
Divorced	-0.665	0.012	-0.654	0.029	-0.665	0.012	-0.654	0.029
Widowed	-0.262	0.523	-0.310	0.504	-0.266	0.517	-0.318	0.493
Cohabitating	0.280	0.206	0.333	0.184	0.277	0.212	0.329	0.190
Neurotic	-0.179	0.016	-0.212	0.011	-0.184	0.013	-0.224	0.008
Returns×Up Dummy	1.955	0.035	4.293	0.002				
Returns×Down Dummy	-3.033	0.000	-4.555	0.000				
Returns×Up Dummy×Neurotic	0.053	0.960	0.034	0.984				
Returns×Down Dummy×Neurotic	-0.065	0.935	0.637	0.615				
Returns 5-day×Up Dummy					-4.735	0.028	-1.867	0.559
Returns 5-day×Down Dummy					-0.657	0.698	-1.130	0.660
Returns 5-day×Up Dummy×Neurotic					1.452	0.550	2.701	0.472
Returns 5-day×Down Dummy×Neurotic					-0.956	0.619	-2.560	0.397
Marginal R^2	2.1%		2.4%		2.1%		2.3%	
Conditional R^2	45%		51%		45%		51%	

5. Discussion

Our findings confirm that, as Karlsson et al. (2009) and Sicherman et al. (2013) have claimed, individual investors do indeed selectively monitor their portfolios as a function of market conditions. However, our observations differ markedly from those described before. The Vanguard and Swedish Premium Pension Authority datasets show that logins increase as returns move from negative to positive, whereas in our dataset portfolio monitoring increases as daily market returns move away from zero in either direction, indicating that the ostrich metaphor is inappropriate for our data. That is, rather than decrease portfolio monitoring when market conditions are negative and increase monitoring when market conditions are positive, we find that our sample of investors increased monitoring both when market conditions were positive *and* when they were negative. We term this phenomenon the meerkat effect to highlight the contrast with the previous observations of reduced monitoring (as apocryphal meerkats stick their heads up to look around whenever something happens). Our meerkats are logging-in to gain information (either to inform their decision making or for its own sake) and, unlike the ostriches from the Vanguard and Swedish Premium Pension Authority data sets, do not avoid negative information. This pattern of increased monitoring as a function of both increasing and decreasing daily market returns also holds when we consider 5-day and 20-day moving averages for the daily market returns.

Our meerkat effect has an asymmetry, with logins increasing more for positive returns than negative returns (the asymmetric V-shape in Figures 3 and 6). One possible cause of this asymmetry, suggested to us by Duane Seppi, is that the differential response to positive and negative market returns might be indicative of two effects, one of which masks the other: an effect on information monitoring that increases with changes in market returns in either direction and a hidden underlying ostrich effect that somewhat suppresses monitoring when returns are negative. Despite the possibility of a latent ostrich effect, in the plots of logins by daily returns there is, nonetheless, evidently a clear difference between the login behaviour we report here and that found in the earlier studies showing an ostrich effect. For Sicherman et al. (2013, Figure 9) this shows fewer logins when returns are negative and more logins when returns are positive. For us, the scatter plot in Figure 3 shows more logins for increasing positive and increasing negative returns. Even accepting that there may be an underlying ostrich effect in our data leaves substantial differences between the data sets.

When we exclude those logins that involved trades from our dataset we again observe a meerkat effect - increasing non-trade logins for both rising and falling markets - *for immediate* (daily) returns. However, for returns over a longer (5-day) time periods we found a different pattern for non-trade logins - they reduced for negative weekly market returns – an ostrich effect. Nonetheless we again consistently observed statistically significant meerkat-like increasing logins with both up *and* down Friday market returns for weekend and double weekend logins when the markets are closed and investors cannot trade. Clearly the portfolio monitoring behavior observed here is qualitatively quite different to that observed by Karlsson et al. (2009) confirmed by Sicherman et al. (2013).

While there are differences between our data set and the Vanguard and Swedish Premium Pension Authority datasets, we all find that portfolio monitoring varies in relation to market movements. If, as Karlsson et al. (2009) and Sicherman et al. (2013) argued, the cause of variation in portfolio monitoring is psychological in nature then we might expect to see some association with psychological characteristics of our investors. Consistent with this rationale we find that the personality trait of neuroticism accounts for the behavioral heterogeneity on an individual basis and interacts with daily market returns in predicting investors' portfolio monitoring decisions. The more neurotic investors generally login less often than their less neurotic counterparts but, more interestingly, neuroticism interacts with the observed variation in logins with daily market returns. Investors generally increased their logins for negative market returns but neurotic investors increased their logins more than non-neurotic investors. For positive market returns, as described above, investors also generally increased their logins but neurotics were less responsive and increased their logins more gently than non-neurotic investors. These findings corroborate the notion of Karlsson et al. (2009) and Sicherman et al. (2013) that variation in portfolio monitoring is attributable to psychological factors – and this can be understood in terms of the different utility that different individuals may experience from any anxiety arising from contemplating portfolio performance.

Although our investigation focuses on the same behaviors as those studied by Karlsson et al. (2009) and Sicherman et al. (2013), we have noted that there are a number of differences between the datasets. Such results could be due to differences between the samples studied across the two studies – the Karlsson et al. (2009) and Sicherman et al.'s (2013) samples consisted of Swedish and USA nationals investing in their own pensions, which might perhaps entail more critical investments and with different time horizons than was at stake for the present sample who were not directly investing for their pensions and may have been involved in more discretionary trades. A clear difference in the behavior of the samples is evident when we compare the daily proportion of logins across the different datasets. From Karlsson et al.'s paper we can infer that the proportion of daily logins in the US dataset was about 2% and for the Swedish data was about 0.2% (Karlsson et al. Table 1), while in our sample the daily login base-rate is 37%.

Although Karlsson et al. (2009) and Sicherman et al. (2013) gave evidence in support of the rationale for observing an ostrich effect there is also evidence, cited by these authors, that people will sometimes hasten the experience of unpleasant experiences. In the introduction we referred to the study by Berns et al. (2006) who observed that people preferred more pain - a higher voltage shock - in order to reduce the time they spent dreading an impending shock. Of course the circumstances of this study are rather different to those of investors exhibiting the ostrich or meerkat effects. Nonetheless it may be that our investors who were likely trading over shorter time horizons than the Vanguard and Swedish Premium Pension Authority investors were more likely to feel that they should get any bad news over with; while the Vanguard and Swedish Premium Pension Authority investors, trading for their pensions, might have felt more able to defer monitoring poor portfolio performance in the short term.

The present study is not the only research finding at variance with the ostrich effect. Brown and Kagel (2009) used a trading laboratory experiment to test participants' information acquisition behavior. In their experiment participants chose one of twenty stocks to hold in 8 trials with 20 periods in each trial. At the end of each round participants were given the performance of their chosen stock and an option to view the past performance of the other nineteen stocks. Consistent with selective avoidance of negative information, the authors expected investors with losing stock to ignore the performance of other stocks that were not chosen so as to avoid the fear and the regret associated with learning that they made the wrong investment. However, their results indicate that, when holding a declining stock, a majority of participants sought more information about the performance of the other stocks they could have invested into; but when holding a winning stock, only a minority of participants chose to look at the performance of the other un-chosen stocks.

In Brown and Kagel's experiment, for a majority of decisions, participants chose to ignore information that could potentially have led to higher earnings. Plainly, this trade-off of the informational value of information against its hedonic impact raises questions about the implications of this phenomenon for financial practice. In relation to the financial markets Caplin and Leahy (2001) have even incorporated anxiety into the expected utility model and argued that it could account for the equity premium puzzle (Mehra & Prescott 1985; Benartzi & Thaler 1995). Similarly, Borghans, Duckworth, Heckman and ter Weel (2008) highlight the importance of personality in predicting various social and economic outcomes including the labour market, crime, educational attainment, schooling decisions, health and longevity, and suggest that personality traits should be incorporated into conventional economic models. Likewise, we have shown the role of individual differences and their importance in information acquisition decisions. With regards to financial markets, inconsistent information acquisition will be reflected in prices; consequently understanding fully how people respond to information is clearly vital to being able to predict prices and dynamics of the financial markets and the economy.

Acknowledgments

We thank the Behavioral Finance team at Barclays Wealth Management for their help. We also gratefully acknowledge editors and the two anonymous reviewers for invaluable comments and suggestions as well as George Loewenstein for his generous discussion, Duane Seppi for his suggestions and Martijn van den Assem for his contribution. This research was supported by ESRC grants RES-062-23-0952, RES-000-22-3339, and ES/K002201/1, and Leverhulme grant RP2012-V-022.

References

Benartzi, S., Thaler, R., 1995. Myopic loss aversion and the equity premium puzzle. The Quarterly Journal of Economics 110, 73-92.

Berns, G. S., Chappelow, J., Cekic, M., Zink, C., Pagnoni, G., Martin-Skurski M., 2006. Neurobiological substrates of dread. Science 312, 754-758.

Brock, T., Balloun, J.L., 1967. Behavioral receptivity to dissonant information. Journal of Personality and Social Psychology 6, 413–428.

Borghans, L., Duckworth, A., Heckman, J., ter Weel, B., 2008. The economics and psychology of personality traits. Journal of Human Resources 43, 972-1059.

Brown, A. L., Kagel, J. H., 2009. Behavior in a simplified stock market: the status quo bias, the disposition effect and the ostrich effect. Annals of Finance 5, 1-14.

Caplin, A., Leahy, J., 2001. Psychological expected utility theory and anticipatory feelings. Quarterly Journal of Economics 116, 51-80.

Cobb-Clark, D., Schurer, S., 2011. The stability of big-five personality traits. IZA Discussion Paper 5943.

Costa, P. T. Jr., McRae, R. R., 1992. Revised NEO personality inventory manual. Odessa, FL: Psychological Assessment Resources, Inc.

Dorn, D., Huberman, G., 2005. Talk and action: what individual investors say and what they do. Review of Finance 9, 437-481.

Ehrilch, D., Guttman, I., Schonbach, P., Mills, J., 1957. Post-decision exposure to relevant information. Journal of Abnormal and Social Psychology 54, 98–102.

Galai, D., Sade, O., 2006. The "Ostrich effect" and the relationship between the liquidity and the yields of financial assets. The Journal of Business 79, 2741-2759.

Glaser, M., Weber, M., 2007. Overconfidence and trading volume. Geneva Risk and Insurance Review 32, 1-36.

Graham, J. R., Harvey, C., 2001. The theory and practice of corporate finance: evidence from the field. Journal of Financial Economics 60, 187-243.

Heineck, G., Anger, S., 2010. The big-five trait taxonomy: history, measurement, and theoretical perspectives. In Pervin, L., John, O. (Eds.). Handbook of Personality: Theory and Research, 2nd Ed. New York: Guilford Press, 102-138.

Karlsson, N., Loewenstein, G., Seppi, D., 2009. The ostrich effect: selective attention to information. Journal of Risk and Uncertainty 38, 95-115.

Lins, K., Servaes, H., Tufano, P., 2010. What drives corporate liquidity? An international survey of strategic cash and lines of credit. Journal of Financial Economics 98, 160-176.

Loewenstein, G., Read, D., Bausmeister, R., 2003. Time and decision: economic and psychological perspectives on intertemporal choice. Russell Sage Foundation, NY, USA.

Loewenstein, G., 2006. The pleasures and pains of information. Science 312, 704-706.

Matthews, G., Deary I. J., Whiteman, M.C., 2003. Personality traits. Cambridge: Cambridge University Press.

McGinnis, E., 1949. Emotionality and perceptual defence. Psychological Review 56, 244-251.

Mehra, R., Prescott, E. C., 1985. The equity premium: a puzzle. Journal of Monetary Economics 15, 145-161.

Mueller, G., Plug, E., 2006. Estimating the effects of personality on male and female earnings. Industrial and Labor Relations Review 60, 3-22.

Nyhus, E. K, Pons, E., 2005. The effects of personality on earnings. Journal of Economic Psychology 26, 363-384.

Postman, L., Bruner, J. S., McGinnis, E., 1948. Personal values as selective factors in perception. Journal of Abnormal Psychology 43, 142-154.

Sicherman, N., Loewenstein, G., Seppi, D., Utkus, S., 2013. Financial Attention. Working paper.

Watt, C., Morris, R., 1995. The relationships among performance on a prototype indicator of perceptual defence/vigilance, personality, and extrasensory perception. Personality and Individual Differences 19, 635–648.

Williams, J. M. G., Watts, F. N., MacLeod, C., Matthews, A., 1988. Cognitive psychology and emotional disorders. Chichester, England: Wiley.

Wilt, J., Oehlberg, K., Revelle, W., 2011. Anxiety in personality. Personality and Individual Differences 50, 987-993.